

ENHANCED LOCAL BINARY PATTERNS FOR AUTOMATIC FACE RECOGNITION

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ABSTRACT

This paper presents a novel automatic face recognition approach based on local binary patterns (LBP). LBP descriptor considers a local neighbourhood of a pixel to compute the features. This method is not very robust to handle image noise, variances and different illumination conditions. In this paper, we address these issues and extend the original LBP operator by considering more pixels and different neighbourhoods to compute the feature vector. The proposed method is evaluated on two benchmark corpora, namely UFI and FERET face datasets. We experimentally show that our approach is very efficient because it significantly outperforms several other state-of-the-art methods and is efficient particularly in the real conditions where the above mentioned issues are obvious.

Index Terms— E-LBP, Enhanced Local Binary Patterns, Face Recognition, Czech News Agency, Local Binary Patterns, LBP

1. INTRODUCTION

Automatic face recognition (AFR) consists in person identification from digital images using a computer. This field has been intensively studied during the past few decades and its importance is constantly growing particularly due to the nowadays security issues.

It has been proved that LBP is a very efficient image descriptor for several tasks of computer vision field [1] including automatic face recognition [2]. It considers a very small local neighbourhood of a pixel to compute the feature vector. The individual values are then computed using the differences between intensity values of the central and surrounding pixels.

In this paper, we propose a novel face recognition approach called *Enhanced local binary patterns (E-LBP)*. This method improves the original LBP operator by considering larger central area and larger neighbourhood to compute the feature vector. These properties keep more information about the image structure and can compensate some noise, image

variance issues and the differences between train / test images. Note that this method of computation of the LBP operator considering more points has, to the best of our knowledge, never been done before and it is thus the main contribution of this paper.

The proposed method is evaluated on two standard corpora, UFI [3] and FERET [4] face datasets. These corpora have been chosen to show the results in two particular cases: face recognition in real conditions and one training sample issue. The results of this work will be used by Czech News Agency (ČTK)¹ to automatically annotate people in photos during insertion into the photo-database.

The rest of the paper is organized as follows. Section 2 describes the most important methods based on LBP. Section 3 details the proposed approach. Section 4 first describes the corpora used for evaluation and then presents the results of experiments realized on this data. The last section discusses the results and proposes some future research directions.

2. RELATED WORK

Methods based on local binary patterns generally use LBP histograms computed in rectangular regions [2]. The concatenated histogram values create face representation vectors which are then compared using several distance metrics as for instance histogram intersection or Chi square distance [5]. An interesting LBP extension which is proposed by Ojala in [1] are uniform local binary patterns. This approach reduces the histogram size to 59 by grouping the rarely occurring cases into one value. Li et al. propose dynamic threshold local binary pattern (DTLBP) [6]. They use the mean value of the neighbouring pixels and also the maximum contrast between the neighbouring points to compute the feature vector. Another LBP extension are local ternary patterns (LTP) [7] which uses three states to capture the differences between the central pixel and the neighbouring ones. The authors claim that both DTLBP and LTP are less sensitive to the noise than the original LBP method.

Local derivative patterns (LDP) are proposed in [8]. The

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difference from the original LBP is that it uses the features of higher order. It thus can represent more information than the original approach. Davarzani et al. propose in [9] a weighted and adaptive LBP-based texture descriptor. This approach successfully handles some issues of the previously proposed LBP-based approaches such as invariance to scaling, rotation, viewpoint variations and non-rigid deformations.

Elongated Binary Patterns (ELBP) [10] is another variant of the LBP using an elliptical instead of circular neighbourhood. The main advantage of this modification is that it retains better structural information in the images. Jin et al. propose in [11] improved local binary patterns (ILBP). This method compares the intensities of neighbourhood pixels against the local mean pixel intensity (instead of the intensity of the central pixel). This reduces the effect of noise.

Another interesting LBP adaptation proposed by Li et al. is extended local binary patterns [12]. This method introduces two different and complementary feature types (pixel intensities and differences). Experimental results demonstrate significant improvements over the classical LBP approach in texture classification task.

The previously described methods were oriented to the modification of the LBP operator itself, however creation of the feature vector and matching procedure remain always similar. Both tasks are significantly improved in [13] by automatic identification of the important facial points using Gabor wavelets and k-means clustering algorithm. The feature vectors are then created in such positions and the features are compared individually (instead of creation of one large vector). It was experimentally shown that this method is very efficient on several standard face corpora.

For additional information about the LBP based methods, please refer to the surveys [14, 15].

3. ENHANCED LOCAL BINARY PATTERNS FOR FACE RECOGNITION

3.1. Local Binary Patterns

We extend the original LBP algorithm, therefore, it is shortly described next and also illustrated in Figure 1. The original LBP operator uses a 3×3 square neighbourhood centred at the given pixel. The algorithm assigns either 0 or 1 value to the 8 neighbouring pixels by Equation 1.

$$N = \begin{cases} 0 & \text{if } g_N < g_C \\ 1 & \text{if } g_N \geq g_C \end{cases} \quad (1)$$

where N is the binary value assigned to the neighbouring pixel, g_N denotes the gray-level value of the neighbouring pixel and g_C is the gray-level value of the central pixel. The resulting values are then concatenated into an 8 bit binary number. Its decimal representation is used to create the feature vector.

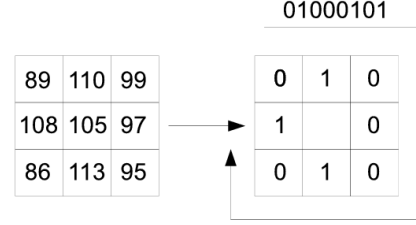


Fig. 1. An example of the feature computing by the original LBP operator

3.2. Enhanced Local Binary Patterns

We extend the original LBP operator by computing the feature values from point-sets instead of the isolated points. We also consider the different sizes of the neighbourhood of the central area. This concept can handle several LBP issues:

- LBP has small spatial support, therefore it cannot properly detect large-scale textural structures;
- It loses local textural information, since only the signs of differences of neighbouring pixels are used;
- It is very sensitive to noise, because the slightest fluctuation above or below the value of the central pixel is treated as equivalent to a major contrast between the central pixel and its surroundings.

Let G_N be a set of neighbouring pixel intensities with its centre C_N , let G_C be a set of central pixel intensities with its centre C_C and r be the distance between the centres C_N and C_C . We calculate the representative values for these sets as averages of the pixel intensities belonging to these sets: $g'_N = \text{mean}(G_N)$ and $g'_C = \text{mean}(G_C)$.

The feature vector is then created in a similar way as in the case of the original LBP operator using g'_N and g'_C values instead of g_N and g_C , respectively (see Section 3.1).

Note that it is possible to consider several point-set topologies of different sizes to capture different texture information, however in this paper we use only the square shapes of the sizes 2×2 , i.e. 4 points and 3×3 points, i.e. 9 points.

The proposed operator is further denoted as $E\text{-LBP}_{x,y,r}$, where $x \in \{4, 9\}$ represents the neighbouring pixel-set topology, $y \in \{4, 9\}$ is the central pixel-set topology and r is the distance between the centres C_N and C_C , which is hereafter called *E-LBP range*. This procedure is depicted in Figure 2.

3.3. Face Modelling & Recognition

We compute LBP values in all points of the face image. The image is then divided into a set of square cells lying on a regular grid. Feature vectors are computed for each cell as a histogram of the $E\text{-LBP}$ values. Every cell is then represented by one feature vector of the size 256. As many other LBP face recognition methods, we concatenate the feature histograms

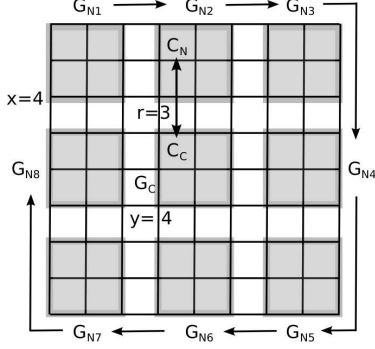


Fig. 2. Scheme of E-LBP_{4,4,3} operator

into one feature vector to create the face model. We use histogram intersection distance [5] for the face recognition.

4. EVALUATION

4.1. Experimental Set-up & Corpora

We used OpenCV² toolkit for implementation of our experiments.

4.1.1. UFI Dataset

Unconstrained facial images (UFI) dataset [3] contains face images of 605 persons extracted from real photographs. The training set contains about 7 images per person while one face image is designed for testing. There are two different partitions available. In the following experiments, we use *Cropped images dataset* which is composed of the face image in resolution 128×128 pixels. Figure 3 (left) shows two images of one individual from this partition with recognition results of our method.

4.1.2. FERET Dataset

FERET dataset [4] contains 14,051 images of 1,199 individuals. In this paper, we use *fa* set for training while *fb* set for testing of the proposed method which represents 1195 of different individuals to recognize. Note that only one image per person/set is available therefore we address the one training sample problem. For the following experiments, the faces are cropped according to the eye positions and resized to 130×150 pixels. Figure 3 (right) shows two example images of one person from the FERET database with recognition results obtained by the proposed approach.

4.2. Optimal Cell Size of the Proposed Operator

The cell size (see Section 3.3) is one key parameter of the proposed approach. We will thus identify its optimal value. We also would like to show the robustness of the proposed

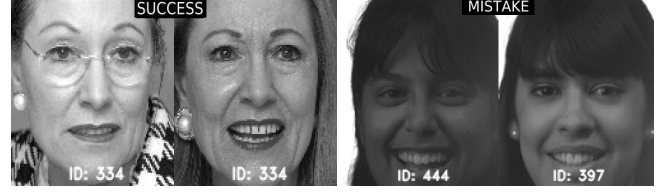


Fig. 3. Example images of one person from the UFI (left, correct recognition) and FERET (right, recognition error) datasets

operator, therefore we will determine one common value for both corpora. The results of this experiment are depicted in Figures 4 and 5 for UFI and FERET datasets, respectively.

These figures show that this parameter significantly influences the performance of the whole algorithm and its optimal configuration is beneficial. They further show that the proposed E-LBP operator outperforms the original LBP on both corpora, which is particularly evident in the case of the UFI dataset containing real-world images. We further look at the optimal values on both corpora which is 15 and 8 points for UFI and FERET, respectively. We also would like to favorize smaller operator sizes for faster computation. Therefore, we chose for the following experiments the cell size 10 points.

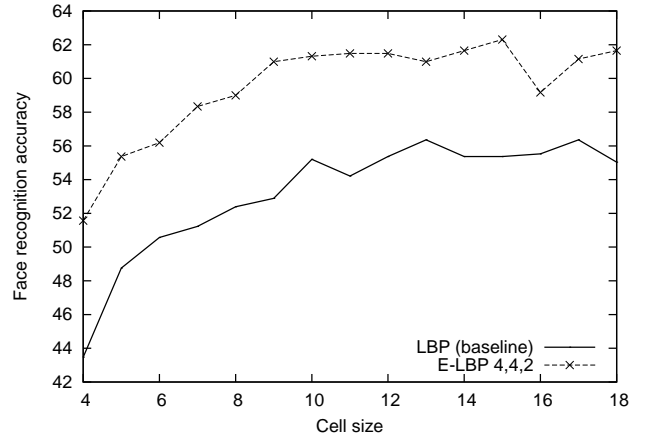


Fig. 4. Face recognition accuracy on UFI dataset depending on the cell size

4.3. Optimal Range of the Proposed Operator

E-LBP range (see Section 3.2) is another important parameter of the proposed method. Therefore, we will determine its optimal value for both corpora in the second experiment (see Fig. 6 for UFI and Fig. 7 for FERET dataset). We can thus summarize:

- The optimal E-LBP range is 5 for both corpora;
- The best topology is E-LBP_{4,9} for both corpora;
- The results of E-LBP_{4,4} are almost similar as E-LBP_{4,9};

²<http://opencv.org/>

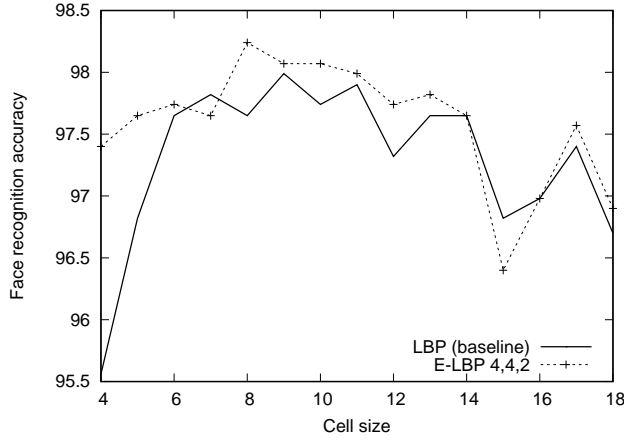


Fig. 5. Face recognition accuracy on FERET dataset depending on the cell size

- Proposed E-LBP operator significantly outperforms the baseline LBP in these two cases on both corpora;
- The behaviour of this operator on both corpora is consistent (similar progress).

We conclude that the proposed E-LBP operator is very robust and we also assume that it should perform well on other corpora using these settings.

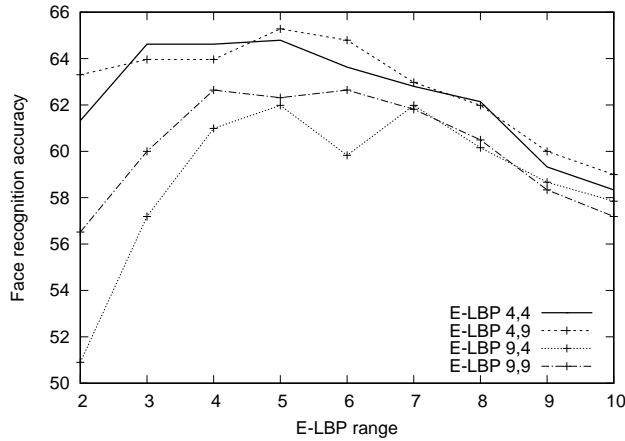


Fig. 6. Face recognition accuracy of the proposed method on UFI dataset depending on the E-LBP range

4.4. Final Results

Table 1 compares the performance of the proposed method against several other state-of-the-art algorithms. It demonstrates that the proposed approach is very efficient, which is particularly evident in the real conditions (i.e. UFI dataset), where it outperforms the standard LBP by 10% and the previous best method by 2% in absolute value.

This method also achieves competitive recognition rate on FERET dataset (one training sample issue). Although the

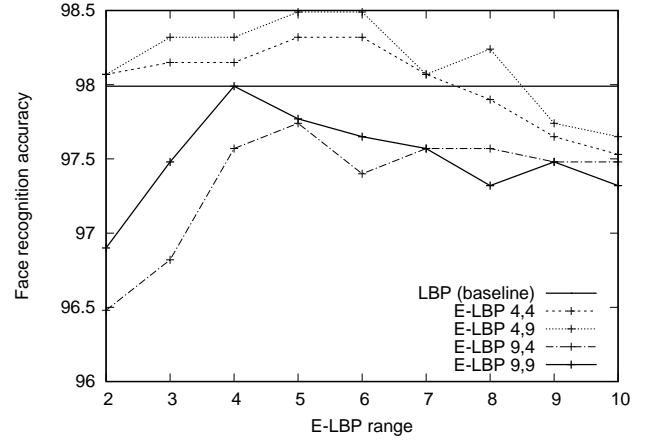


Fig. 7. Face recognition accuracy of the proposed method on FERET dataset depending on the E-LBP range

score is not the highest one, it is comparable with the best method, because the difference is not statistically significant.

Approach	Recognition rate [%]	
	UFI	FERET
SRC (Wagner et al. [16])	-	95.20
LGBPH (Yao et al. [17])	-	97.00
LBP (Ahonen et al. [2])	55.04	93.89
LDP (Lenc et al. [3])	50.25	-
LDP (Zhang et al. [8])	-	94
FS-LBP (Lenc et al. [13])	63.31	98.91
E-LBP _{4,9,5} (proposed)	65.28	98.5

Table 1. Final results of the proposed approach on the UFI and FERET databases against several state-of-the-art methods

5. CONCLUSIONS AND FUTURE WORK

This paper introduced a novel face recognition approach based on LBP. We proposed an original operator which considers more pixels and different neighbourhoods to compute the feature vector. We evaluated this method on the standard UFI and FERET face datasets. We experimentally showed that our approach is very efficient, because it outperforms several other state-of-the-art methods (LBP included) and its capabilities are particularly evident in the real conditions.

The first perspective consists in evaluation of different point-set topologies (see Section 3.2) to compute the feature vector. Then, we will modify the matching method as suggested in [13]. We also would like to evaluate the proposed method on some other corpora and also on other tasks (e.g. texture classification or object recognition) to demonstrate its robustness and applicability to other domains.

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